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APPLICATION OF MODIFIED (PSO) AND SIMULATED ANNEALING ALGORITHM (SAA) IN ECONOMIC LOAD DISPATCH PROBLEM OF THERMAL GENERATING UNIT

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ABSTRACT

This paper deals with the problem of economic load dispatch (ELD) in thermal generating unit. The main issue of generating unit to minimize the cost of generation so modified Particle Swarm Optimization (PSO) method is proposed for solving this issue. The modified PSO method was developed through simulation of a simplified social system and has been found to be robust in solving continuous nonlinear optimization problems in terms of accuracy of the solution and computation time The proposed algorithm is applied for the ELD of six unit thermal plant systems and the performance of the proposed modified PSO method is compared with the Simulated Annealing Algorithm (SAA). All results obtained through MATLAB Simulink software. The comparison of results shows that the proposed modified PSO method was indeed capable of obtaining higher quality solutions efficiently for ELD problems within less computation time.

Key words*:* Economic Load Dispatch (ELD), Particle Swarm Optimization (PSO), Simulated Annealing Algorithm (SAA), MATRIX LABORATORY (MATLAB).

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1. INTRODUCTION

The Economic Load Dispatch (ELD) problem is one of the fundamental issues in power system operation. The main objective is to reduce the cost of energy production taking into account the transmission losses. While the problem can be solved easily if

the incremental cost curves of the generators are assumed to be monotonically increasing piece-wise linear functions, such an approach will not be workable for nonlinear functions in practical systems. In the past decade, conventional optimization techniques such as lambda iterative method, linear programming and quadratic programming have been successfully used to solve power system optimization problems such as Unit commitment, Economic load dispatch, Feeder reconfiguration and Capacitor placement in a distribution system. For highly non-linear and combinatorial optimization problems, the conventional methods are facing difficulties to locate the global optimal solution. Recently there is an upsurge in the use of modern evolutionary computing techniques in the field of power system optimization. Particle Swarm Optimization (PSO), first introduced by Kennedy and Eberhart, is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous non-linear optimization problems. The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristics than other stochastic methods. All the particles in PSO are kept as members of the population through the course of a run (a run is defined as the total number of generation of the evolutionary algorithms prior to termination). It is the velocity of the particle which is updated according to its previous best position of its companions.

The proposed method results have been compared with the Simulated Annealing Algorithm (SAA). Simulated Annealing (SA) has been proved to be effective and quite robust in solving the optimization problems. SA can provide near global solutions and can also handle effectively the discrete control variables. SA does not stick into local optima because SA begins with many initial points and search for the most optimum in parallel. SA considers only the pay-off information of objective function regardless whether it is differentiable or continuous. Consequently, the most realistic cost characteristic of power plants can be formulated. Simulated Annealing (SA) is a stochastic optimization technique which is based on the process of annealing in Thermodynamics proposed by Kirkpatrick. Mathematical model of simulated annealing describes how the molecules of liquidated metal move freely with respect to each other and by gradually cooling (thermodynamic process of annealing) thermal mobility are lost. The atoms start to get arranged and finally form crystals, having the minimum energy which depends on the cooling rate.

2. MATHEMATICAL MODEL

A. Objective function

The objective of the economic load dispatch is to minimize the generating cost based on the premise that constraints are satisfied. Coal consumption (standard coal) is selected as the optimization objective in order to emphasize the main aspects, simplify the mathematical model and make the problem comparable. Then the mathematical description of ELD's objective function is:

The objective of the ELD problem is to minimize the total fuel cost. Mathematically it can be represented as

$$\text{Minimize} \quad C_t = \sum_{i=1}^{n} C_i\,(P_i) \tag{1}$$

$$C_t = \sum_{i=1}^{n} a_i\,P_i^{\,2} + b_i\,P_i + c_i \tag{2}$$

Where C_t Fuel cost of the system.

C_i Fuel cost of the generating unit of the system. a_i , P_i andc_i are cost coefficients of generator i.

P_i Output power generation of unit i.

The ELD problem is subjected to the following constraints, the power balance equation,

$$\sum_{i=1}^{n} P_{Gi} = P_D + P_L \quad (3)$$

The total Transmission loss,

$$P_L = \sum \sum P_m B_{mn} P_n \quad (4)$$

In addition, power output of each generator has to fall within the operation limits of the generators as shown below,

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (5)$$

In the power balance criterion, an equality constraint must be satisfied, as shown in equation (3). The generated power should be the same as the total load demand plus total line

Losses .The generating power of each generator should lie between maximum and minimum limits represented by equation (5), where *Pi* is the power of generator *i* (in MW); *n* is the number of generators in the system; PD is the system's total demand (in MW); *PL* represents the total line losses in (MW) and *min Pi* and *max Pi* are, respectively, the output of the minimum and maximum operation of the generating unit i in (MW).

3. OVERVIEW OF PSO

PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles change their position (states) with time. In PSO system particles fly around in a multi- dimensional search space. During flight, each particle adjusts its position according to its own experience and the experience of neighbouring particles, making use of the best position encountered by it and neighbours. The swarm direction of a particle is defined by the set of particles neighbouring the particle and its history experience. Instead of using evolutionary operation to manipulate the individuals, like in other evolutionary computational algorithms, each individual in PSO flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and its companions flying experience.

Let *x* and *v* denote a particle co-ordinate (position) and its corresponding flight speed (velocity) in a search space respectively. Therefore, each ith particle is treated as a volume less particle, represented as xi= (xi1, xi2 …xid) in the d -dimensional space. The best previous position of the ith particle is recorded and represented as pbesti=(pbesti1,pbesti2,…….. pbestid).The index of the best particle among all the particles is treated as global best particle, is represented as gbestd. The rate of velocity for particle 'i' is represented as vi= (vi1, vi2……...vid). The modified velocity and position of each particle can be calculated using the current velocity and the distance from pbestid to gbestd as shown in the following formulas,

$$V_{id}^{(t+1)} = \omega V_{id}^{(t)} + C_i\, rand\,()\left(pbest_{id} - P_{gid}^{(t)}\right) + C_2\, Rand()\left(gbest_{id} - P_{gid}^{(t)}\right) \quad (7)$$

$$P_{gid}^{(t+1)} = P_{gid}^{(t)} + V_{id}^{(t+1)} \quad (8)$$

In the above equation, C1 has a range (1.5, 2), which is called self-confidence range; C2 has a range (2, 2.5), which is called swarm range.

The parameter Vd ^{max} determines the resolution, or fitness, with which regions are to be searched between the present position and the target position .If Vd ^{max} is too high, particles may fly past good solutions. If Vd ^{max} is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, Vd ^{max} was often set at 10-20% of the dynamic range on each dimension.

The constants C1and C2 pull each particle towards pbest and *gbest* positions. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions. Hence, the acceleration constants C1 and C2 are often set to be 2.0 according to past experiences. Suitable selection of inertia weight ' ω ' provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, ω often decreases linearly from about 0.9 to 0.4 during a run. In general, the inertia weight *w* is set according to the following equation,

$$\omega = \omega_{max} - \left[\frac{\omega_{max}-\omega_{min}}{it_{max}}\right] * it \quad (9)$$

where ω - inertia weight factor

ω_{max} - maximum value of weighting factor

ω_{min} - minimum value of weighting factor

it_{max} - maximum number of iterations

it - current number of iteration

4. APPLICATION OF PSO METHOD TO ECONOMIC LOAD DISPATCH

In population based optimization algorithm, there is an avid necessity of improving the performance of existing algorithm. This can be implemented by two means. Either the basic operators of algorithm should be redesigned or proper tuning of adjustable parameters should be done. In proposed variant of PSO, proper tuning of adjustable parameters like w, c1 and c2 are done so that it can reach on optimal solution as early as possible. In existing PSO, the values of adjustable parameters like w,c1 and c2 are independent from the values of gbest and pbest. This is the main reason why PSO converges very slow toward optimal solution. These values are may remain fixed or may vary according to the number of generation. In proposed algorithm, a relationship has been established between adjustable parameters and the values of gbest and pbest and the values of w, c1 and c2 are set accordingly. The value of c1 has been set to pbestval-out /gbestval and c2 has been set to repmat (gbestval,ps,1)-out /gbestval so that particles may exploit good solutions as early as possible. Moreover to improve convergence rate of the algorithm a very high inertia weight equivalent to gbestval-pbestavg/gbestval has set. These values motivate particles to exploit solution around good regions and capture optimal solution as early as possible. The PSO algorithm was utilized mainly to determine the optimal allocation of power among the units, which were scheduled to operate at the specific period, thus minimizing the total generation cost.

A. Calculation process of the proposed method

This paper presents a quick solution to the constrained ELD problem using the PSO algorithm to search optimal or near optimal generation of each unit. The sequential steps of the proposed PSO method are given below.

Step 1: Initialize randomly the individuals of the population according to the limit of each unit including individual dimensions, searching points, and velocities. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step 2: To each chromosome of the population the dependent unit output Pd will be calculated from the power balance equation and Bmn coefficient matrix.

Step 3: Calculate the evaluation value of each individual Pgi, in the population using the evaluation function C given by (2).

Step 4: Compare each individual's evaluation value with its *pbest.* The best evaluation value among the pbests is denoted as *gbest.*

Step 5: Modify the member velocity *v* of each individual *Pg*, according to equation (7)

Step 6: Check the velocity components constraint occurring in the limits from the following conditions,

If $V_{id}{}^{(t+1)} > V_d{}^{max}, then\ V_{id}{}^{(t+1)} = V_d{}^{max}$,

$V_{id}{}^{(t+1)} > V_d{}^{min}, then\ V_{id}{}^{(t+1)} = V_d{}^{min}$,

Where

$V_d{}^{min} = -0.5\ P_g{}^{min}$

$V_d{}^{max} = +0.5\ P_g{}^{max}$

Step 7: Modify the member position of each individual *Pg* according to (8)

Step 8: If the evaluation value of each individual is better than previous *pbest*, the current value is set to be *pbest*. If the best *pbest* is better than *gbest*, the value is set to be *gbest*.

Step 9: If the no.of iterations reaches the maximum, Go to step 10.Otherwise, go to step 2.

Step 10: The individual that generates the latest *gbest* is the optimal generation power of each unit with the minimum total generation cost.

5. OVERVIEW OF SIMULATED ANNEALING ALGORITHM (SAA)

Simulated Annealing (SA) algorithm is a nature-inspired method which is adapted from process of gradual cooling of metal in nature. In the metallurgical annealing process, a solid is melted at high temperature until all molecules can move about freely and then a cooling process is performed until thermal mobility is lost. The perfect crystal is the one in which all atoms are arranged in a low level pattern, so crystal reaches the minimum energy. It is basically a stochastic optimization technique which is based on the principles of statistical engineering. The search for global minima of a multidimensional function is quite a complex problem especially when a big number of local minima correspond to the respective function. The main purpose of the optimization is to prevent hemming about to local minima. The

originality of the SA method lies in the application of a mechanism that guarantees the avoidance of local minima.

A. The Process of Annealing in Thermodynamics

At high temperature, the metal is in liquid stage. The molecules of liquidated metal move freely with respect to each other, via gradual cooling (thermodynamic process of annealing) thermal mobility is lost. The atoms start to get arranged and finally form crystals, having the minimum energy which depends on the cooling rate. If the temperature is reduced at a very fast rate, the crystalline state transforms to an amorphous structure, a meta-stable state that corresponds to a local minimum of energy. Annealing process of metal influences SA algorithm. If the system is at a thermal balance for given temperature *T*, then the probability *PT(s)* that it has a configuration *s* depends on the energy of the corresponding configuration *E(s)*, and is subject to the Boltzmann distribution:

$$\mathbf{P_T(s)} = \frac{\mathbf{e}^{\frac{\mathbf{E(S)}}{\mathbf{KT}}}}{\sum_{\mathbf{w}} \mathbf{e}^{\frac{\mathbf{-E(w)}}{\mathbf{KT}}}} \tag{10}$$

Where, *k* is the Boltzmann constant and the sum $\sum_w$ includes all possible states *W*. Metropolises were the first to suggest a method for calculating a distribution of a system of elementary particles (molecules) at the thermal balance state. Let the system has a configuration *g*, which corresponds to energy E(g). When one of the molecules of the system is displaced from its starting position, a new state σ occurs which corresponds to energy E(σ). The new configuration is compared with the old one. If E(σ)≤ E(g) , then the new state is accepted. If E(σ)>E(g), then the new state is accepted with probability :

$$\frac{\mathbf{e}^{-(\mathbf{E(\sigma)-E(g)})}}{\mathbf{kT}} \tag{11}$$

Table 1 Connection between Thermodynamic and Combinatorial Optimization:

Thermodynamics simulation	Combinatorial Optimization
System state	Feasible Solutions
Energy	Cost
Change of state	Neighboring Solutions
Temperature	Control Parameter
Frozen state	Heuristic Solution

B. Control parameters of SA algorithm

For the successful application of the SA algorithm is the annealing schedule is vital, which refers to four control parameters that directly influence its convergence (to an optimized solution) and consequently its efficiency. The parameters are the following:

a) Starting Temperature

b) Final Temperature

c) Temperature Decrement

d) Iterations at each Temperature

a) Starting Temperature The starting temperature must be set to a big enough value, in order to make possible a big probability of acceptance for non optimized solutions during the first stages of the algorithm's application. However, if the value of the starting temperature gets too big, SA algorithm becomes non-effective because of its slow convergence and in general, the optimization process degenerates to a random walk. On the contrary, if the starting temperature is low then there is a greater probability of achieving local minima. There is no particular method for finding the proper starting temperature that deals with the entire range of problems.

b) Final Temperature During the application of the SA algorithm it is common to let the temperature fall to zero degrees. However, if the decrement of the temperature becomes exponential, SA algorithm can be executed for much longer time. Finally, the stopping criteria can either be a suitable low temperature or the point when the system is "frozen" at current temperature.

c) Temperature Decrement Since the starting and final temperatures have been defined, it is necessary to find the way of transition from the starting to the final temperature. The way of the temperature decrement is very important for the success of the algorithm suggested the following way to decrement the temperature:

$$T(t) = d/\log(t) \quad (12)$$

Where *d* is a positive constant.

An alternative is the geometric relation: **T(t)=a.t** (13)

Parameter *a*, is a constant near 1. In effect, its typical values range between 0.8 and 0.99.

d) Iterations at each Temperature

For increased efficiency of the algorithm, the number of iterations is very important. Using a certain number of iterations for each temperature is the proper solution. The temperature decrement should take place at a really slow pace that can be expressed as

$$T(t)=t/(1+\beta t) \quad (14)$$

Where, β takes a very low value.

SA Algorithm Implementation of ELD Problems

Step 1: Initialization of temperature, *T*, parameter α (α is a constant smaller than but close to 1), and maximum number of generations. Find, randomly, an initial feasible solution, which is assigned as the current solution *Si* and perform ELD in order to calculate the total cost.

Step 2: Set the iteration counter to *i*=1

Step 3: Find a neighbouring solution *Sj* through a random perturbation of the counter one and calculate the new total cost, *Fcost*.

Step 4: If the new solution is better, we accept it, if it is worse, we calculate the deviation of cost $\Delta S=Sj-Si$ and generate a random number uniformly distributed over $\Omega\in (0, 1)$.

If $e^{\frac{-\Delta s}{t}} \geq \Omega\in (0, 1)$. Accept the new solution *Sj* to replace *Si.*

Step 5: If the stopping criterion is not satisfied, reduce temperature using parameter α:

T(t) =α. t and return back to Step 2.

6. RESULT

To verify the feasibility of the proposed modified PSO method, six generating unit and ten generating unit has been taken into consideration.

Case 1: for 6 generating uni:tThe result of Proposed method and Simulated Annealing (SA) algorithm is compared in the following tables(1) :-

$P_{D=}$ 700 (MW)	P_L (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Cost (Rs/Hr)	i
M PSO	19.42	28.103	10.000	118.28	118.58	232.05	212.42	36912.22	6000
SAA	19.43	28.29	10.00	118.9	118.6	230.7	212.7	36912.52	242216

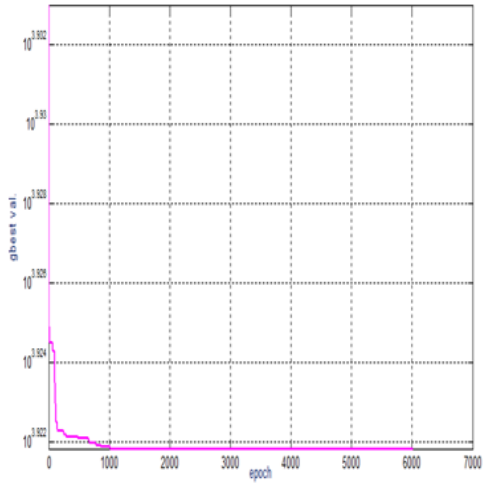

Figure 1. Convergence characteristics of 6 unit system (PD=700MW)in case (pso).

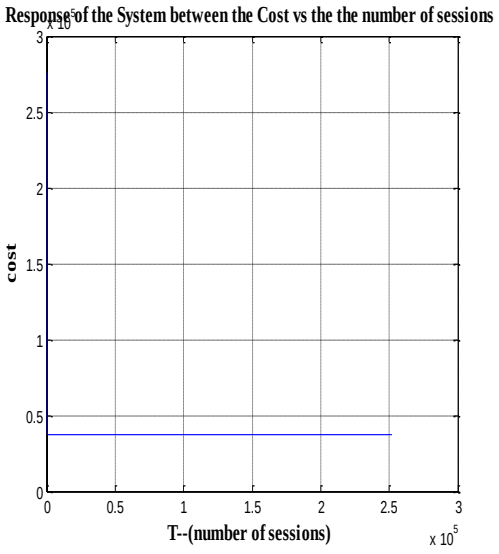

Figure 2 Convergence characteristics of 6 unit system (PD=700MW) in case (SAA).

Case 2:for 10 Generating unit The result of Proposed method and Simulated Annealing (SA) algorithm is compared in the following tables(2) :-

$P_D = 2000$ (MW)	P_L (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	P7 (MW)	P8 (MW)	P9 (MW)	P10 (MW)	Cost (Rs/Hr)	i
Modified PSO	87.017	55	80	106.86	99.315	82.932	83.853	300	339	470	470	111266.1	5000
SAA	83.236	54.99	77.658	104.96	103.55	160.00	187.28	240.27	264.63	440.05	449.80	114383.8	28523

From the comparative analysis of above table it is clear that the number of iteration and the cost of modified PSO is less than the number of iteration and the cost of SAA method.

7. CONCLUSION

In this paper, the proposed modified PSO method was successfully employed to solve the ELD problem with all the constraints and compared with the Simulated Annealing algorithm (ASS). The proposed method has been demonstrated to have superior features including high quality solution, stable convergence characteristics, and less computation time. Many non-linear characteristics of the generators can be handled efficiently by the proposed method. The comparison of results for the test cases clearly shows that the proposed method was indeed capable of obtaining higher quality solution efficiently for ELD problems.

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REFERENCES

[1] Bakirtzis, V. Petridis, and S. Kazarlis, Genetic algorithm solution to the economic dispatch problem, *IEE proceedings on Gen., Transm. Dist.*, vol. 141, No.4, pp. 377-382, July 1994.

[2] D. C.Walters and G. B. Sheble, Genetic algorithm solution of economic dispatch with valve point loading, *IEEE Trans. on Power Systems*, vol.10, No.8, pp. 1325-1332, Aug. 1993.

[3] R. C. Eberhart and Y. Shi, Comparison between genetic algorithms and particle swarm optimization, *Proceedings of IEEE Int. Conference on Evolutionary Computation*, pp.611–616, May 1998.

[4] M. Sudhakaran, Dr S M R Slochanal, Integrating Genetic Algorithms and Tabu Search for Emission and Economic Dispatch Problems", *IE (I) Journal –EL*, vol 86, pp.39-43, June 2005.

[5] Nidul Sinha, Chakrabarti.R, and Chattopadhyay.P.K, Fast Evolutionary Computing Techniques for Short-Term Hydrothermal Scheduling, *IEEE Trans. on Power Systems*, vol.18, No.1, pp. 214-220, February 2003.

[6] Y. Shi and R. Eberhart, A modified particle swarm optimizer, *Proceedings of IEEE Int. Conference on Evolutionary Computation*, pp.69-73, May 1998.

[7] P. J. Angeline, Using selection to improve particle swarm optimization, *Proceedings of IEEE Int. Conference on Evolutionary Computation*, pp. 84-89, May 1998.

[8] P. Venkatesh, Dr P S Kannan, M Sudhakaran, Application of Computational Intelligence to Economic Load Dispatch, *IE (I) Journal–EL* Vol 81, pp.39-43, September 2000.

[9] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, and Y. Nakanishi, A particle swarm optimization for reactive power and voltage control considering voltage security assessment, *IEEE Trans. on Power Systems*, vol.15, No.4, pp. 1232–1239, Nov. 2000.

[10] Zwe-Lee Gaing, Particle Swarm Optimization to solving the Economic Dispatch Considering the Generator Constraints, *IEEE Trans. On Power Systems*, Vol.18, No.3, pp. 1187-1195, August 2003.

[11] Bo Lu and Mohammad Shahidehpour, Unit Commitment with Flexible Generating Units, *IEEE Trans. on Power Systems*, Vol.20, No.2, pp. 1022-1034, May 2005.

[12] Yong Fu, Mohammad Shahidehpour and Zuyi Li, Security Constrained Unit commitment with AC constraints, *IEEE Trans. on Power Systems*, Vol.20, No.3, pp. 1538-1550, August 2005.

[13] Kamlesh Kumar Vishwakarma, Hari Mohan Dubey, Simulated Annealing Based Optimization for Solving Large Scale Economic Load Dispatch Problems. International Journal of Engineering Research & Technology (IJERT) Vol. 1 Issue 3, May - 2012 ISSN: 2278-0181.

[14] Ashish Dhamanda and A.K. Bhardwaj, Automatic Generation Control of Thermal Generating Unit by Using Conventional and Intelligent Controller. *International Journal of Electrical Engineering & Technology*, **5**(10), 2014, pp. 56–64.

[15] Sanjay Mathur, Shyam K. Joshi and G.K. Joshi, Development of Controller For Economic Load Dispatch by Generating Units Under Varying Load Demands. *International Journal of Electrical Engineering & Technology*, **4**(4), 2013, pp. 159–171.

[16] Mr.Vijay Kumar, Dr.Jagdev Singh, Dr.Yaduvir Singh, Dr.Sanjay Sood, Design & Development of Genetic Algorithms for Economic Load Dispatch of Thermal Generating Units. *International Journal of Computer Engineering & Technology*, **3**(1), 2012, pp. 59–75

[17] M. Venkatesh, Ramakrishna Raghutu. Economic Load Dispatch Using Simulated Annealing Algorithm. International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056 Volume: 02 Issue: 03 | June-2015.